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Rotor Fault Analysis in Doubly Fed Induction Generator Using Wavelet Analyser

Dr. P. Vinoth Kumar, Associate Professor, Geethanjali Institute of Science and Technology. Nellore.
P. Ranjith Krishna, Assistant Professor, Mahatma Gandhi Institute of Technology, Hyderabad.
Dr. Thummala Ravikumar, Associate Professor, Geethanjali Institute of Science and Technology. Nellore.

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Abstract:
The analysis of a transient existence in a DFIG connected wind turbine with suitable methodologies paves an appropriate solution for electrical and mechanical fault analysis. This paper analysis the signal faults that occur in Doubly Fed Induction generator (DFIG) that facilitates condition monitoring and rectifies the problems, generates more power with less cost. Because of the alternating nature of wind speed, its addition to the grid is quiet challenging due to power quality and stability. For the large penetration of wind energy that is obtained from the DFIG, the wavelet analyser entrenched to the wind power system, offers profound perception to the transient signals. The work is first simulated and the results are represented onto the wavelet analyser for accurate exposure, detection and better resolution of the characters of rotor current signal. Analysing rotor current signal from simulation with the wavelet analyser available in the MATLAB, it is examined that the occurrence of lower frequency bandwidth signals accompanies comparatively more energy and larger magnitude wavelet coefficients. These wavelet coefficients are responsible for the stability and quality of the signals. The investigated technique is a combination of the Continuous Wavelet technique with the electric signals obtained from the DFIG that helps in deep analysis and deformation of the fault signal into the original signal.

Keywords:*Doubly Fed Induction generator (DFIG), wavelet analyser, Continuous* Wavelet technique, *fault analysis.*

INTRODUCTION

Electrical energy becomes inevitable in today's scenario. Though various sources are available to produce electrical energy, wind becomes the affordable energy producing system. The technological development enhances the energy generating process as an easier one. Still it has certain drawbacks such as sudden variation in wind speed that creates the certain problems in the power generating. More researches are going on machine modelling, power converters control and monitoring and conditioning techniques. This paper analysis the signal faults that occur in Doubly Fed Induction generator (DFIG) that facilitates condition monitoring and rectifies the problems, generates more power with less cost.

DFIG has a power electronic device connected which controls the rotor current and speed. Between DFIG and rotor of the wind turbine a drive train is connected that increase the speed of the DFIG rotor. The torque of the DFIG depends on the wind and shaft rotation speed of generator. The rotor side converter connected facilitates the regulation of torque and reaction power injection of DFIG provides stationary output with less expense and minimized power loss [1][2].

Though DFIG has advantage of simple construction, better efficiency because of fewer harmonic injected into the grid, it has disadvantages of complex control and need of protection because stator is connected to the grid. Since stator is coupled to electrical network in a straight it is more sensitive to electrical network.

In wind energy conversion the reliability and efficiency plays a vital role for extracting the high power output. Analysing the fault signal in DFIG provides the opportunity for economic benefits by protecting itself avoiding the risk of unwanted oscillations [2].

There are different types of faults occurs in DFIG when connected with the wind energy source. Unexpected load variations and sudden variation in wind speed at severe conditions lead to disturbance of rotor torque successively cause the power waving of the entire system reducing potency and lifelong. This usually occurs at low inertia wind turbine [3].

DFIG connected with the grid face challenge with the safety as the fault current must be identified and reduced soon as possible. The highest possibility of faults occur in the DFIG rotor and it undergoes the more stress when there is mechanical and electrical fault. Sensors connected to the stator or rotor measure the signal and help to find the fault in the signal and it give the chance to detect the current and voltage. On investigation of the detected signal a suitable current can be provided for exciting the rotor enables the generation of constant torque. This paves the way for energy output stationary and provides maximum output even in variable wind speed and load variation. The vibration of high speed shaft leads to the vibration of wind turbine drive train. It becomes necessary to analyse the vibration and hence vibration sensors plays role in analysing the high frequency aspects related to mechanical unbalance conditions of the drive train. But there are issues related to the vibration sensors that are placed at high towers and difficult to access [2][3][4]. To find the immediate shaft revolving speed of the rotor, speed detection is required that is important for fault diagnosing. Though the sensors are essential for fault analysis, the use of sensors increases the expenditure, makes bulky and wiring convolution. At an equivalent time it causes the extra problems associated with the dependableness of the turbine system once the sensing device is failing [5].

Instead of taking the sensors signals taking the current signals provide the advantages such as sensors less control or data acquisition devices provide the cost reduction and reduces the complexity in control. Conditional monitoring controls the sudden failure and costly repair. It enables the efficiency of the system and it enhances the working of the system for long duration. Different observance methods are available for a non stationary signal generation at DFIG output. The signals obtained from the DFIG are non stationary and it is difficult to extract the fault wherever specifically occurred from the signals since it varies with relation to time. Fault monitoring for non stationary signal is usually performed with the electric signal parameters like current, voltage, power with the signal processing methodologies such as instantaneous frequency, power signature analysis, Short-time Fourier transform[6][16].

Instantaneous frequency analysis has limitations in its time-frequency resolution capability and Power signature analysis is reliable but needed additional condition monitoring equipments [7]. Analysing electrical faults is easy but the mechanical faults in the drivetrain can be analysed with the electrical quantities in trending now. The disadvantage with the Short-time Fourier transform can analyse only the non-stationary signals [8].

But condition monitoring can provide only the information of the fault signal but it cannot separate the fault signal from the output signal. In addition to the signal condition monitoring the signal classification with the help of the Wavelet analysis for both the stationary and non-stationary waveforms analysed provides more advantages [9]. In this work the rotor current signals are classified with the wavelet analysis that provides the great opportunity for investigating the fault.

Wind turbine condition monitoring Challenges

The wind turbine on exposed to the sudden wind fluctuations, lightning strikes and load variation when connected to the grid cause severe effect on the power electronic interface connected to the DFIG. It leads to the continuous maintenance and reliability becomes the challenging issue. Instead of analysing the mechanical parameters electric signals are taken for the condition monitoring but it does not become popular due to lack of knowledge by the industry experience [2]. The analysis of the signals obtained in time domain analysis at the commencement of the fault it indicates with the parameters such as vibration level obtained. Though it is easy to access its accuracy level is affected by wind direction and wind speed. Frequency domain analysis techniques such as envelope analysis, spectrum analysis and spectral Kurtosis are based upon the fast Fourier transform (FFT)[10].

Splitting up the fault from the vibration signals obtained from the drivetrain can be done with the envelope and spectral analysis based on the FFT. It is applicable to only the Stationary signals. Even though FFT simple to analyse and plays a wide role it is not suitable to DFIG condition monitoring connected to wind turbine because it is non-stationary signal. Hence advancement in the signal analysis method is needed [6]. Many techniques are invented for fault diagnosis but it has difficult calculations. Other disadvantage in implementing the techniques is monitoring the wind turbine condition that does not provide the option successful implementation of the monitoring techniques.

Artificial neural network and genetic algorithm offers the improved chance of analysis of non-linear signals with classification, estimation and fault detection. The techniques can be used in real time for analysing wind turbine faults but drawbacks with these techniques are lack of possibility in proper data collection for analysis. These type algorithms are used in SCADA application where it measures the fault signals with the low frequency and unsuitable for different environmental conditions. The methods based and condition monitoring is currently used in existing wind turbines but with low frequency resolution which does not provide the option for diagnosis and prognosis. Production of signals at higher frequency resolution is affluent for diagnosis but additional process by monitoring methods increase the cost [11] [12].

To process the non-linear fault signals obtained from the DFIG analysis at time and frequency domain becomes mandatory to provide the signal information that is needed to reduce the downtime of the wind turbine. Since the DFIG and the wind turbine are connected to the gear box the sudden wind gust or if any failure occurs in the gearbox and it -will be transmitted to the shaft of the generator. Due to the transmission error in the shaft the vibrations is caused by the fault that will affect the rotor current signals. This provides the chance to identify the fault in mechanical parts by investigating the current signals [13]
When there is fault with the gear box, the measured vibrational signals has an effect with the amplitude and phase modulations that interrupt the rotational frequency. The frequencies in the gear fault can be distinguished into shaft rotating frequency and gear meshing frequency. The high frequency torsional vibrations caused by high speed wind leads the DFIG drivetrain to get stressed and reduce the efficiency and life of the equipment. This torsional vibration paves the electrical power oscillations which causes the serious issues in the power system [14]. The controlling frequencies that are affected by the fault in gearbox and shaft provide the opportunity for drivetrain fault. Due to the uneven speed and meshing of gear vibrations signals are non-stationary and it varies with time. Fourier analysis is insufficient tool and alternate option to be found. The frequency spectrum analysis is does not provide the satisfactory results and signal conditioning is required as solution [15].

Wavelet analysis

DFIG's earlier work on condition management focused on steady-state activity. A new concept based on an analysis of transient rotor currents is presented here. The rotor flux is proportionate to the variability in speed and load, and it also depends on the defective components of

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the amplitude of the rotor current. Analysis of the wavelet signal serves as the best measurement method for tracking wind turbine condition. The wavelet analyzer tool helps to remove the basic component of the current and analyze the residual current using wavelets. FFT analyzer has limited capacity to delete immediate frequency and magnitude data variation from a non-stationary waveform under slip variations [16].

Wavelet analyzer provides the ability to investigate precisely the statistical absorption of short-term events such as the instability interface with a moving rotor blade of the windmill. In this paper, rotor current signals are disintegrated and examined using wavelet analysis techniques at initial progress. The continuous wavelet transformation is used to discuss the results [17]. A novel technique for the fault diagnosis of wind turbine under non-stationary conditions is proposed using a DFIG rotor current signal. The dc offset and high frequency noise of the current signal is first removed in the proposed method. Wavelet analysed to assess the effect of the examined fault rates on the wind turbine driveline to differentiate faults in order to avoid any latent devastating faults decrease operating and repair costs and improve system reliability and accessibility.

Wavelet analyser is a mathematical tool for executing the signal analysis when signal frequency differs. Wavelet analysis delivers more exact and detailed data regarding the signal than other signal analysis techniquesIn this paper, the study of rotor current signal uses ongoing wavelet analyzes that extract specific time-varying patterns in signal and perform time-localized filtering. It helps to investigate signals and images in completely different frame rates in order to observe points of modification, harmonic frequencies and alternative events that are not promptly visible in the data. Comparing multi-scale signal statistics and analyzing current signal information to highlight specific patterns.

Because wavelet analyzer is a robust learning time method–frequency behavior of predetermined electricity signals. The advantages of the Fourier transform wavelet decomposition enable the ability to provide the time-varying or distinctive features. Multiresolution is the part of the wavelet analyzer that has recently found applications in an exceptional area such as lossless compression of data in signal, information and modeling of non-linear signal processes. A DFIG operating in irregularity produces harmonic content in the current generated. Thus, in the near future, rotor current analysis will provide necessary helpful data on the prevalence of machine faults. A comparative study of rotor current behaviour is suggested in this paper, which provides opportunity for analysis of system failure.

Rotor current Signal processing

The rotor current frequency is equivalent to sf in the normal operation of the double-fed induction generator. If the rotor has a split gearbox configuration and abrupt speed fluctuations, the frequency sf rotor current consists of two forward and backward components that produce the ±sf speed fields relative to the rotor speed.

Slip s differ in normal operating state and velocity fluctuations. The reverse travelling wave causes a stator voltage harmonic component at the frequency of infinite inertia drives. Additional harmonics are created because of the interaction of the currents with flux and the inertia-specific speed ripple.

The band currents in the grid side connected windings are mirrored in the main filed and stray flux. Hence a cyclic variation of the grid side connected current causes a torque pulsation at twice the slip frequency 2sf with the corresponding velocity oscillation which is also a function of drive inertia. Speed oscillations that decrease the magnitude of (1-2s)f but power oscillations induce an higher side band current portion at (1 + 2s)f in the winding connected to the grid. It results in current

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components being induced in winding connected to the grid at frequencies (1±2s)f by the weakened wind drivetrain components and sudden speed fluctuations.

Therefore, the evaluation is usually done in the actual signals of the winding connected to grid, but they are non-stationary and it is difficult to extract the fault from the signals specifically because it varies in time. This paper deals with the latest rotor signal analysis, and offers detailed error analysis [18].

Wavelet analysis for simulated DFIG rotor current

The continuous wavelet transform is defined by the following equation:

$$W(c1,c2) = \frac{1}{\sqrt{c1}}\int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{(t-c2)}{c1}dt\right)$$

It is possible to obtain the cwt coefficients C (c1, c2) by continuously changing the scale parameter values, c1, and the position parameter, c2. The vital wavelets of the original signal are given by multiplying the coefficient by the properly scaled and shifted wavelet [19].

(a) Continuous Wavelet 1-D Analysis

Initially, the rotor current signal is imported into the Continuous Wavelet 1-D method, which provides the coefficient plot with the total wavelet coefficients values. The colours are scaled between the minimum and maximum of the coefficients for common methods. The method displays the graph of coefficients, the line plot of coefficients corresponding to the scale[19].

The current signal is set with the sampling period of 1 and the scales are set at initial level where the signal is expanded and coefficients plot is obtained as shown in fig 1.

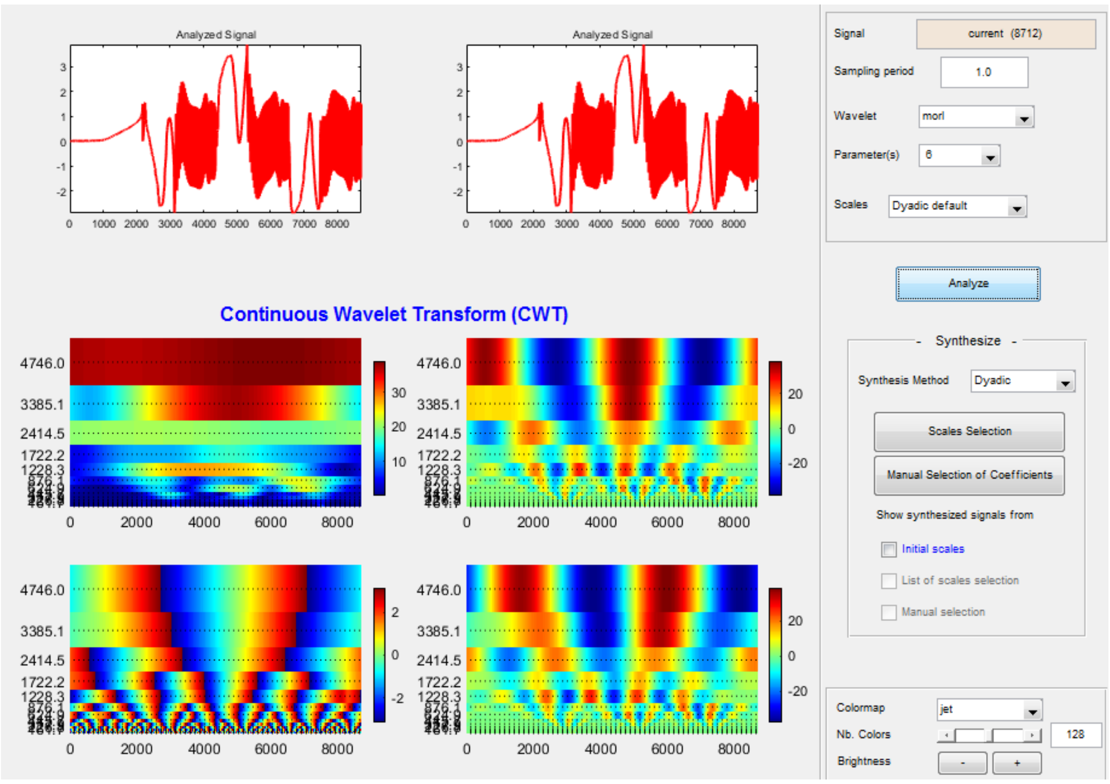

Fig 1: The current signal is set with the sampling period of 1 and the scales are set at initial level

(b)New wavelet for CWT

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With the new wavelet for CWT, the current signal is conferred to estimate a specified pattern with performance improvements providing a permissible wavelet appropriate for pattern detection.

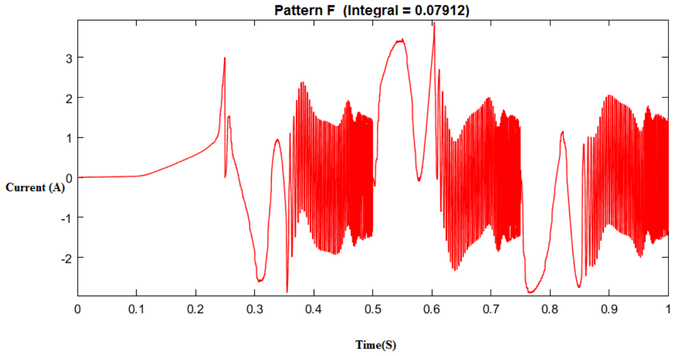

Fig 2: Signal pattern represented by the F with the interval [0, 1] and is of integral 0.07912

Fig 2 displays the selected pattern with the interval [0, 1] represented by the F and is of integral 0.07912. This looks similar to the wavelet but fluctuates. Estimation is made with the 6 polynomial with coherent constraints at the 0 and 1 boundaries to estimate pattern F.

The signal is then generated in computation, enabling the benefits of error detection and correction in transmission as well as data compression over analog storage. New wavelet will be shown along with the original pattern after computation. Now CWT uses the adapted wavelet to detect patterns with the new pattern shown in the figure 3.

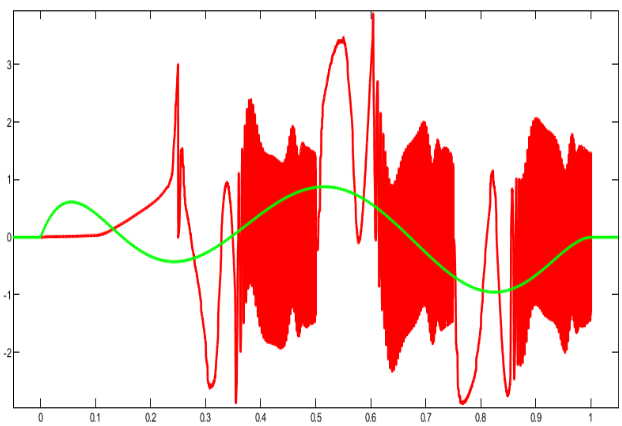

Fig 3: The position and scale detected with (20, 8) and (40, 4)

To define the signal, the adoptive wavelet technique is used. The linear wavelet configuration is tailored to the current vibration signal, exceeding the adaptation parameters of a fixed-shape wavelet. Wavelet performance is adequate, but the denoising effectiveness needs to be suggestively enhanced by adding adaptivity. The running signal is superimposed with two distended and interpreted pattern F versions shown in Fig 4, providing the number of the responses to each individual input signal. Two distended and interpreted versions of pattern F, namely F(t-20)/8) and F(t-40)/4, are superimposed on the running signal. The two pairs identified are given by (20,8) and (40, 4) and are occurred in the CWT graph via dotted lines. The identification is optimal because the two local maxima are fine for the actual values of the continuous wavelet coefficients.

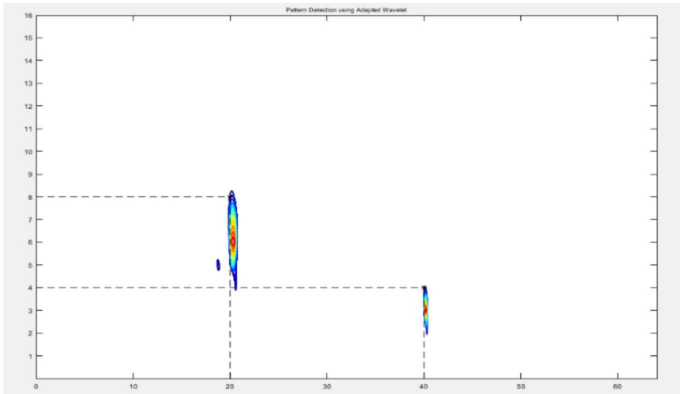

Fig 4: Rrunning signal is superimposed with two dilated and translated versions of the pattern F

N is the addition of additive noise to simulate the impact of several probabilistic reasoning occurring in the signal. Running Signal is given by the formula when {F((t-20)/8)+sqrt(2) times F(t-40)/4) + N} is applied with an additive noise. The detection value is not changed at all, as shown in figure 5.

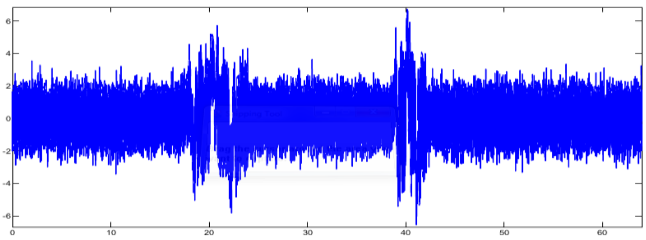

Fig 5: Additive noise added to the signal

The quality correlation of the adaptive wavelet to the well-known wavelets for pattern identification enables the generation of different running signals and the selection of the wavelet to be equivalent to the adapted one shown in Figure 6.

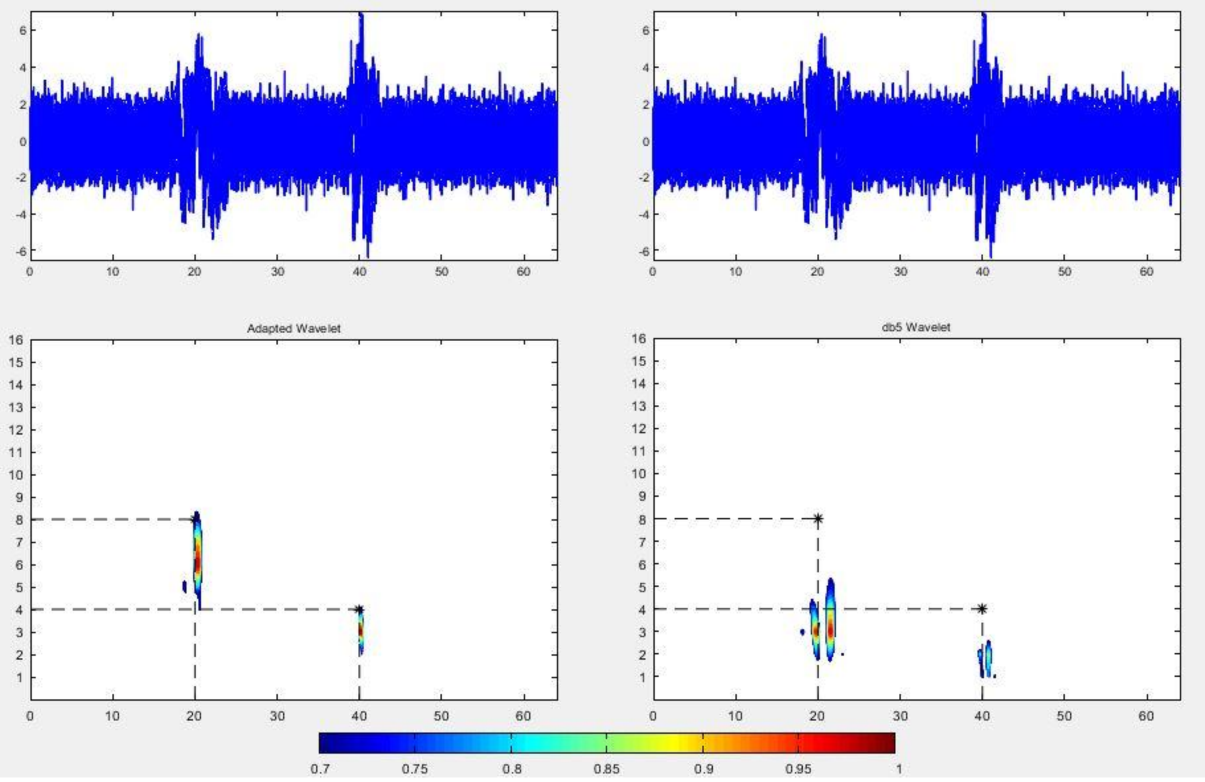

Fig 6: Performance comparison for pattern recognition of the modified wavelet vs well-known wavelets

This method displays pattern recognition on one side with the adapted wavelet and original db1 wavelet on the opposite side. In both cases, the two positions are completely identified, but the db1 wavelet exaggerates the scales marginally. The system allows different running signals to be produced and the wavelet to be correlated with the adapted signal.

b) Denoising

The denoising investigation on the current signal reduces the noise of the high frequency constituents in the signal. The level of decomposition is selected as fourth level according to simulation results as shown in Fig 7.It acts as the essential concept in thresholding because high frequency sub bands consist of the information in the data set. If this data set information is lesser it will be neglected without disturbing the main features of the data set. But this signal information is added with noise, so the coefficient setting is done to zero that removes the noise. Hence to adopt the same threshold value for dealing noise problem in signal analysis noise adopted basis is simulated shown in Fig 8.

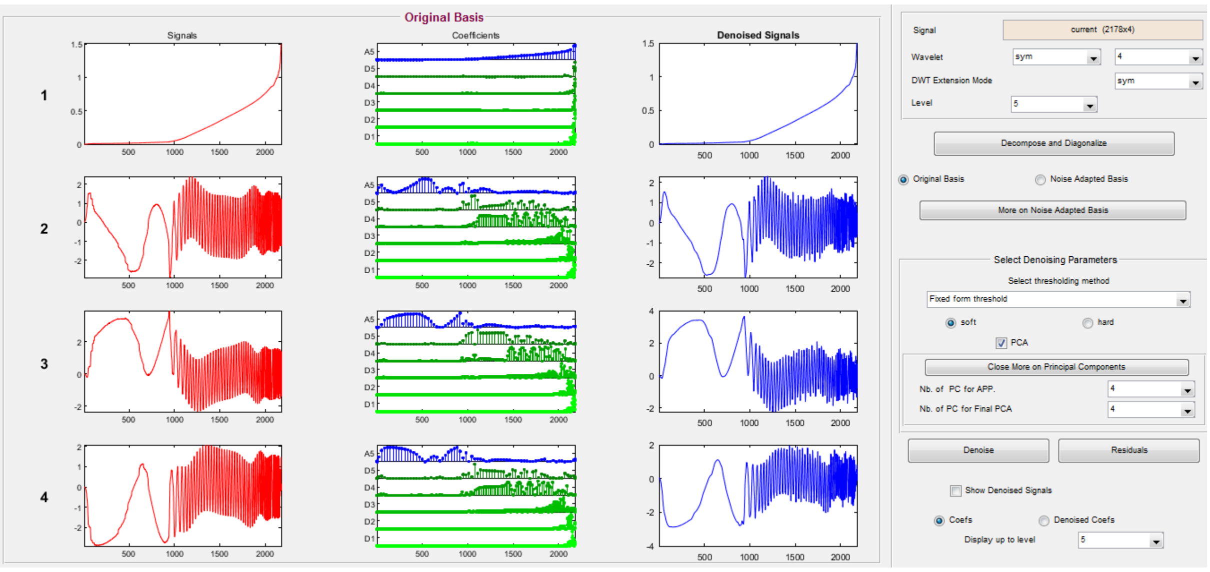

Fig 7: Denoising of signal

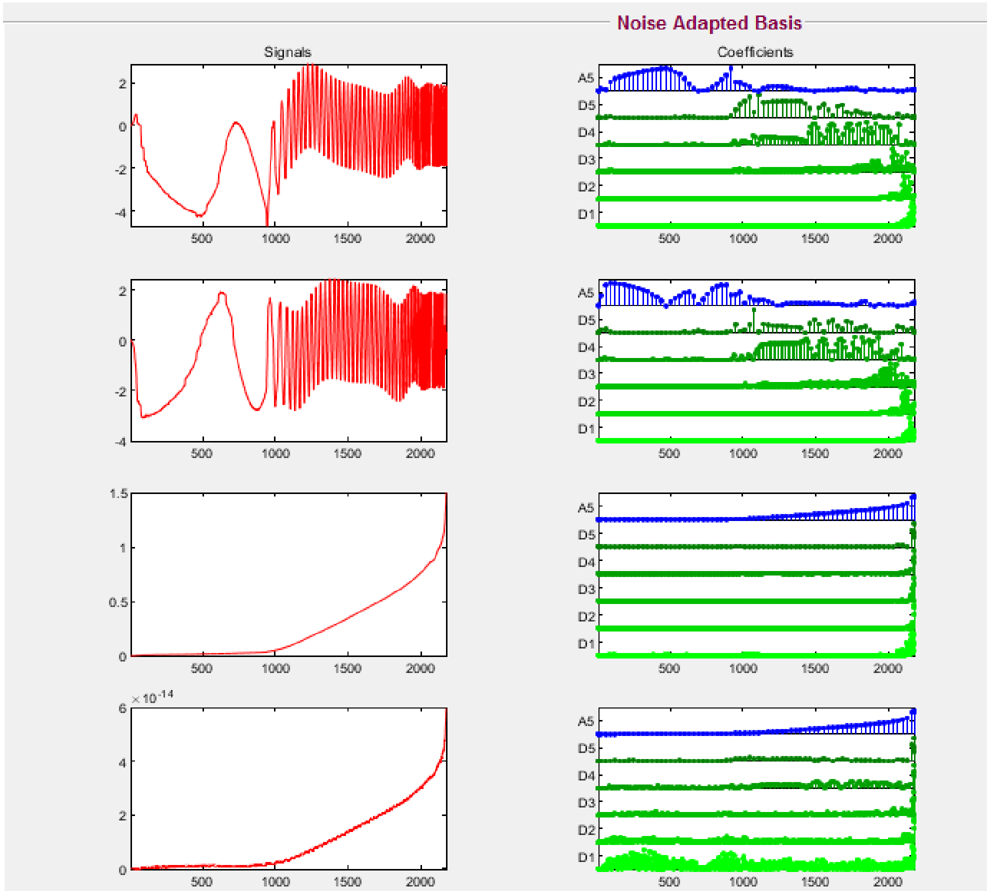

Fig 8: Results obtained on noise adopted basis

The wavelet analyser also facilitates to estimate the zero-shift covariance of input and output noise during the inputs and outputs are measured and processed with the noise estimation. The predictive state estimate depends on initial condition and not on the measurement. The estimation of true state noise covariance matrix helps in the predictor design. The rotor current signal covariance matrix is shown in Fig 9

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Robust Noise Covariance Estimate $\boldsymbol{\Sigma}$

$$\begin{matrix} 0.0000 & 0.0000 & -0.0000 & -0.0000 \\ 0.0000 & 0.0309 & -0.0230 & -0.0079 \\ -0.0000 & -0.0230 & 0.0391 & -0.0161 \\ -0.0000 & -0.0079 & -0.0161 & 0.0240 \end{matrix}$$

Eigenvectors defining the new basis $\mathbf{V}$

$$\begin{matrix} 0.0003 & -0.0002 & 1.0000 & 0.0000 \\ 0.5627 & -0.5917 & -0.0003 & 0.5774 \\ -0.7937 & -0.1914 & 0.0002 & 0.5774 \\ 0.2311 & 0.7831 & 0.0001 & 0.5774 \end{matrix}$$

Eigenvalues $\boldsymbol{\Lambda}$

$$\begin{matrix} 0.0602 \\ 0.0339 \\ 0.0000 \\ 0.0000 \end{matrix}$$

$$\boxed{\boldsymbol{\Sigma} = \mathbf{V}\,\Lambda\,\mathbf{V}^{\mathrm{T}}}$$

Fig 9 : Covariance estiamtion

CONCLUSION

This paper focused on condition testing and prognosis of failures in a wind turbine connected to the DFIG. Continuous Wavelet transformation by the wavelet analyzer implemented on the DFIG rotor current has been suggested to prove that a system based on variance and energy signal analysis of rotor current wavelet decomposition signals is very useful for condition monitoring and failure detection in DFIG. Because the presence of reduced frequency bandwidth signals carries more energy and continues on the wind generator for an extended period of time, which affects the system's stability and quality. The presence of wavelet coefficients of greater magnitude defines the abrupt response that aids in the diagnosis of faults. The proposed work identifies fault levels on the wind energy driveline to distinguish mechanical and electrical faults with the Wavelet analyzer platform's made on the rotor current signal to avoid latent crisis and breakdowns that decrease generating, running costs and improve machine's consistency and accessibility.

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